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Differences between Subjective and Predicted Survival Probabilities and Their Relation to Preventive Care Use

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Abstract: I analyse how differences between subjective and predicted survival probabilities are related to preventive healthcare use. Based on the Health and Retirement Study, I find that private information inherent in subjective survival probability affects the decisions on preventive care use: positive and negative deviations between the subjective and predicted survival probabilities both imply lower likelihood of use, the relations with negative deviations being stronger. These results are driven by perceptions verified by later survival and health outcomes. A theoretical model provides explanation for the empirical results, in which preventive care increases the chances of survival, but the benefits of preventive care also vary with the survival probability.

Keywords: preventive healthcare, private information, subjective survival probability

JEL codes: D84, I12, J14

1 Introduction

The benefits of preventive care services are widely discussed in the medical literature, whereas little is known about the influencing mechanism of subjective survival probability on preventive care use. I analyse this influencing mechanism both empirically and theoretically. The overall effect of subjective chances of survival on the demand for preventive services is not trivial. Higher subjective survival probability can imply higher perceived chances of enjoying the future benefits of preventive care. At the same time, the perceived marginal health benefits of prevention might decrease with higher subjective survival

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probability and thus with better health. People with low longevity expectations might be more desperate to improve their health, thus more willing to use preventive care. However, they might also decide not to use preventive services if they have low chances of survival anyway.

I use data from the Health and Retirement Study (HRS) to estimate the impact of subjective survival expectations on the use of flu vaccination, mammogram, PAP (Papanicolaou) smear, and prostate screening. I focus on expected survival relative to predicted survival probability and estimate the effects of deviations between subjective and predicted survival probabilities on preventive care use. Predicted survival probabilities are based on estimated models of observed survival. Differences between subjective and predictive survivals can stem from biased perceptions, measurement errors, but also from private information. In the rest of the paper I use the term “private information” when I refer to the part of the subjective survival probability which is not due to measurement error but cannot be predicted based on observable characteristics, hence which generally cannot be taken into account when recommendations on preventive care use are made. Distinguishing between positive and negative perceptions allows me to investigate the non-linearities in how subjective survival probability and the private information inherent in these expectations affect preventive care use.

The results indicate that private information inherent in the subjective survival probability affects the decisions on preventive care use, but I find no clear evidence that the use of preventive care is driven by survival perceptions unjustified by later health or survival outcomes. These findings suggest that people use their subjective expectations when they make decisions on preventive care use. When designing and evaluating policies aimed at higher uptake of preventive services, policy makers should take into account that attendance is influenced by private longevity perceptions. Attendance might not be optimal for those who have private information on shorter or longer longevity chances than the population average. Healthcare professionals can provide information about factors affecting the chances of survival (such as the effects of health behaviours and the consequences of certain medical conditions). In turn, correct information can ensure that preventive care use decisions are based on accurate evaluations of the survival probability.

The findings of this paper can enhance our understanding of the demand for preventive care among individuals aged 50 and above. The study also contributes to the usage of survey data on expectations in empirical models of individual choices, corresponding to the recommendations of Manski (2004). The empirical analysis is supported by a model of preventive care demand with uncertain lifetime, which takes into account the mutual relationship between survival probability and preventive care use.

This paper is related to the literature that uses data on subjective survival as an explanatory factor of individual decisions. Although the accuracy of beliefs about subjective survival has been analysed previously (Bago d'Uva et al. 2015; Elder 2013; Hurd and McGarry 1995; Smith, Taylor, and Sloan 2001, among others), looking at the deviations between subjective and predicted survival probabilities in an empirical model of healthcare decisions is a novelty. Bloom et al. (2006) analyse how expected longevity affects retirement decisions and wealth accumulation. Hurd, Smith, and Zissimopoulos (2004) estimate the effect of subjective survival probabilities on retirement and on the claiming of social security benefits. Gan et al. (2015) and Salm (2010) focus on consumption and saving decisions and on bequest motives and how these are affected by subjective mortality expectations. Bíró (2013) estimates the effect of shocks to subjective mortality on consumption expenditures. Fang et al. (2007) look at health investments in relation to subjective longevity, but instead of preventive care use, they focus on smoking, heavy drinking and high BMI. The cited authors generally find that economic decisions are driven by subjective survival probabilities, and using subjective longevity instead of life table data increases the explanatory power of the models.

To my knowledge, this is the first paper to analyse how deviations between subjective and predicted survival probabilities, and in particular, the private information inherent in subjective survival probabilities influence preventive care decisions. This can be considered as an extension of Picone, Sloan, and Taylor (2004), who estimate positive effects of subjective longevity on the attendance of cancer screening, based on the first three waves of the HRS data. They generate an indicator of expected subjective longevity based on survey responses to survival probability, and address the endogeneity of longevity in models of preventive care use (due to reverse causality) with including a measure of time preference in their regressions. Picone et al. also focus on the role of risk and time preference apart from expected longevity. I contribute to their empirical analysis by focusing on the deviations between subjective and predicted survival probabilities, analysing the use of more types of preventive services, and using later waves of the HRS data. As a further extension, I analyse if justified and unjustified survival expectations according to survival and health outcomes have different relations to preventive care use. I can thus investigate non-linear relations between preventive care use and probabilities of survival, and can elicit the role of private information on the chances of survival when decisions on preventive care use are made.

While there are limited results in the literature on the effects of subjective life expectancy on preventive care use, there are more studies which analyse how ageing and the closeness to death is related to preventive care and more generally to healthcare use (Zweifel, Felder, and Meiers 1999; Yang, Norton, and Stearns 2003, among others). Other authors look at the relation between preventive care use and health. For example, Wu (2003) finds that people in poor health are less likely to attend cancer screening, which he explains by psychological factors such as fear and anxiety. This result is in line with the theoretical model of Kőszegi (2003), who shows that anxiety can lead to avoiding doctoral visits or health-related information, but against the recent results of Carman and Kooreman (2014) who report that the perception of more risk makes individuals more likely to use prevention.

The results of Picone et al. (2004) and Wu (2003) suggest that the expected effect of subjective survival probability on preventive care use should be positive. The theoretical model I present in Section 4 reveals that this relation holds only under some specific assumptions. Also, the empirical results of the paper provide mixed evidence, most of the results indicating non-monotonic relations.

The theoretical model of Section 4 is, to my knowledge, the first attempt to explicitly model and analyse the influencing mechanism of subjective survival probability on preventive care use. The model explains how both positive and negative survival perceptions might lead to lower demand for preventive care. A related model is of Picone et al. (2004), deriving a positive effect of longer life expectancy on the probability of attending a cancer screening. However, they consider only the health aspect of expected longevity, they do not model its interaction with the discount rate. I allow the probability of illness and the efficiency of preventive care to vary with the initial probability of survival. I also take into account that while the costs of the prevention are realised in the present, the benefits are realised in the future, which realisation is again conditional on the probability of survival. These extensions lead to different conclusions on the relations between life expectancy and preventive care use than what Picone et al. (2004) find, showing that the relations might be non-monotonic. Another related model is of Balia and Jones (2008), although Balia and Jones focus on the mortality effects of health behaviours, whereas my focus is on the effect of expected survival on the demand for preventive care. Fang et al. (2007) also briefly outline a model that can provide explanation for the so-called Mickey Mantle effect, where greater life expectancy increases investment in health.

The rest of the paper is organised as follows. In Section 2 I introduce the data and discuss how the indicators of positive and negative perceptions in terms of survival probability are generated. Section 3 is devoted to the empirical analysis, and a model of preventive care use with mortality risk is presented in Section 4. Section 5 concludes.

2 Data

I use data from the RAND HRS data collection,[1] version N. This data set is a collection of cleaned and processed variables from the original HRS, which is a US-based panel survey of individuals over age 50 and their spouses. The survey started in 1992 and is repeated every second year. I use data on individuals aged 50 and above from waves 1–11, spanning years 1992–2012.

I focus on four different binary outcome variables, as summarised in Table 1. These indicators refer to preventive care use since the last survey wave, and are asked only from wave 3 on. Every even numbered wave in the preventive care use questions is skipped for individuals who responded in the previous wave. The PAP smear and breast screening questions are asked only of female respondents, prostate screening is asked only of male respondents. Although the HRS data also provide information on cholesterol checks, I do not analyse these because of the low recommended frequency of cholesterol checks (5 years). Reporting no cholesterol checks in a given survey wave could be due to an attendance within the past 5 year, rendering it difficult to draw behavioural consequences from the observations. The analysed service types have different costs and health insurance coverage. Without insurance, according to the information provided by CostHelper.com (2015), the current cost of a flu shot is around \$5–30, mammogram is \$80–120, PAP test is \$25–60, and prostate screening is \$15–250 in case of a digital rectal exam and \$20–120 in case of a prostate-specific antigen test. The insurance coverage changes throughout time. Before the 2010 Affordable Care Act, private health insurance contracts typically provided partial coverage for the costs of flu vaccination and cancer screenings. Medicare Part B also provides annual (bi-annual for PAP test) coverage for the analysed preventive services, although the coverage is

Table 1: Preventive care use in the pooled sample.

	Usage rate	Observations
Flu shot (aged 50 +)	0.602	102,903
Mammogram or X-ray of the breast (women only, aged 50 +)	0.703	58,769
PAP smear (women only, aged 50–65)	0.687	28,935
Prostate screening (men only, aged 50 +)	0.698	43,586

1 The HRS (Health and Retirement Study) is sponsored by the National Institute of Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. The RAND HRS Data file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

only partial (80%) if the prostate cancer test is performed with a digital rectal exam. The Medicaid coverage of preventive services varies by states.

Several agencies provide guidelines of preventive care use (e. g. the United States Preventive Services Task Force, the American Cancer Society, or the Center for Disease Control and Prevention). Generally speaking, the recommended frequency is annual for flu shot and prostate screening, and it is 1–3 years for breast screening and PAP smear. The recommended age categories are universal for flu shots, 40 + for breast screening, 20–65 for PAP smear, and 50 + for prostate screening.

The subjective survival probability measures are based on self-reported survival probabilities to given ages. The question asked is "What is the percent chance that you will live to be age (target age) or more?" The target age varies across the survey waves; it is either age 75, 85, or depends on the current age of the respondent. The age-specific target age is 10–15 years plus the current age. I use the reported survival probability up to the age-specific target age as the basic indicator of subjective survival. If this is missing and the respondent is aged at most 70, or if the survival probability up to age 85 is also missing then I use the survival probability up to age 75. Otherwise I use the subjective survival up to age 85. Based on the selected reported survival probability I generate a k-year subjective survival probability measure, following the hazard scaling approach of Gan, Hurd, and McFadden (2005). This procedure ensures that the survival probability measure I use refers to the same time horizon across all observations. As the first step I calculate the individual specific index of pessimism (η) which is the ratio between the logarithm of the reported survival probability (s) and the life table survival probability (S) from the current age (t) to the target age ($t + a$):

$$\eta_i = \frac{\ln s_{it}^{t+a}}{\ln S_t^{t+a}}.$$

I use the gender-specific period life table for year 2000 as provided by the Social Security Administration (Bell and Miller 2005). If $s = 0$ then the reported zero probability is replaced with 1% survival probability to ensure that the index of pessimism is not missing for these respondents.[2] The k-year subjective survival probability is then calculated as

$$s_{it}^{t+k} = \left(S_t^{t+k}\right)^{\eta_i}.$$

2 Similar replacement procedures are applied by Khwaja, Sloan, and Chung (2007) and Salm (2010). The conclusions of the paper still hold if the $s = 0$ observations are omitted – the main results are qualitatively robust. The results of the paper are also robust to the exclusion of respondents aged 80 and above, for whom there are on average larger discrepancies between the subjective and life table survival probabilities (Figure 1).

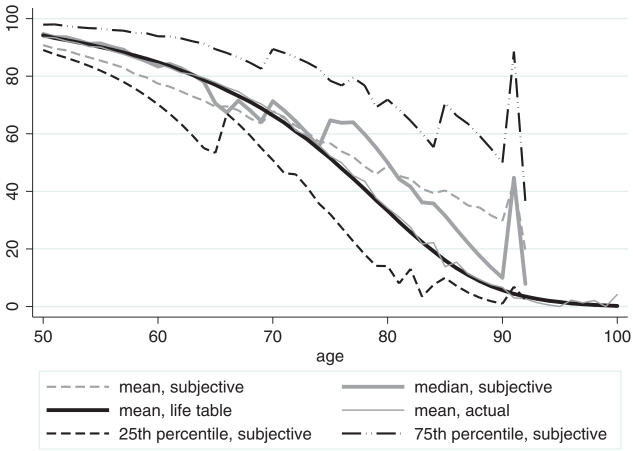

Figure 1: Subjective, life table and actual 10-year survival probabilities (%).

Figure 1 shows that the mean and the median of the so generated subjective 10-year survival probability fit relatively well on the life table survival probability, although the dispersion increases at older ages. The oldest are also more likely to overestimate their chances of survival as compared to the life table probabilities, although the deviations can partly be due to selectivity in answering the survival probability survey question. Hurd and McGarry (1995) and Smith et al. (2001) show that the subjective probabilities of survival are not only comparable to population averages of survival but also vary with observable characteristics the similar way as actual outcomes do.[3]

The subjective survival probabilities can also be compared to the observed survival probabilities in the sample as the HRS data include information if the attrition from the sample was due to death. In Figure 1 I also present the age-specific observed survival rates ("mean, actual"), which are in line with the life table survival probabilities.

Table 2 presents some descriptive statistics of the survival probability indicators and the rest of the variables used in the empirical analysis. These statistics refer to the pooled 50+ sample of waves 1–11.

While η nets the survival probability only from the gender-specific life table survival probability, I generate the indicators of positive and negative perceptions

3 Using the 10-year survival probability as a single indicator of subjective chances of survival is a data-driven simplification. In principle, the whole distribution of survival probabilities influences the preventive care decisions.

Table 2: Descriptive statistics, pooled sample.

	Mean	Std. Dev.
Subjective survival probability	0.699	0.286
Predicted survival probability	0.663	0.298
Positive survival perceptions (if not zero)	0.192	0.195
Negative survival perceptions (if not zero)	0.185	0.172
Female	0.557	0.497
College or higher education	0.396	0.489
Total annual household income (thousand USD)	54.563	185.028
Age	66.989	10.727
White/Caucasian	0.754	0.430
Black/African American	0.180	0.284
Has child	0.927	0.261
Widowed	0.189	0.391
Single	0.140	0.347
Retired (employment status is retired only)	0.358	0.479
Smoked ever	0.581	0.493
Any ADL limitations (difficulties with bathing, eating, dressing, walking across a room, getting in or out of bed)	0.175	0.380
Ever had cancer	0.122	0.328
Ever had diabetes	0.172	0.377
Ever had high blood pressure	0.507	0.500
Ever had heart problems	0.223	0.416
Ever had lung disease	0.085	0.279
Ever had stroke	0.080	0.271
Hospital stay, previous 2 years (1 = yes/0 = no)	0.255	0.436
Nursing home stay, previous 2 years (1 = yes/0 = no)	0.038	0.190
Subjective health (from 1 = excellent to 5 = poor)	2.870	1.149
Covered by Federal Government health insurance	0.594	0.491
Covered by health insurance from current or previous employer	0.341	0.474
Mother alive	0.209	0.406
Father alive	0.081	0.274

by netting out the effects of other observable characteristics as well. The aim is to arrive at a measure that captures that part of the survival expectation which does not follow from other observed characteristics, and which is generally known only to the individual and not to other parties (policy makers) who might make recommendations on preventive care use. First, I estimate gender-specific probit models of the actual 10-year survival, including age, age squared, race, logarithmic income, education level, having children, marital status, employment status, indicator of being a smoker ever, subjective and objective health indicators, health insurance coverage, and indicators of whether the parents are alive as regressors. If non-missing, I also include binary indicators of flu vaccination, mammography, PAP smear and prostate screening from the last two survey waves. The estimated marginal effects are presented in the online Appendix. Then I predict based on these models the 10-year survival probability.[4] Figure 2 shows the histogram of the difference between the subjective and predicted 10-year survival probability (called as net indicator henceforth) – this is centred around zero, reflecting that on average the subjective probabilities correspond to the predicted ones.

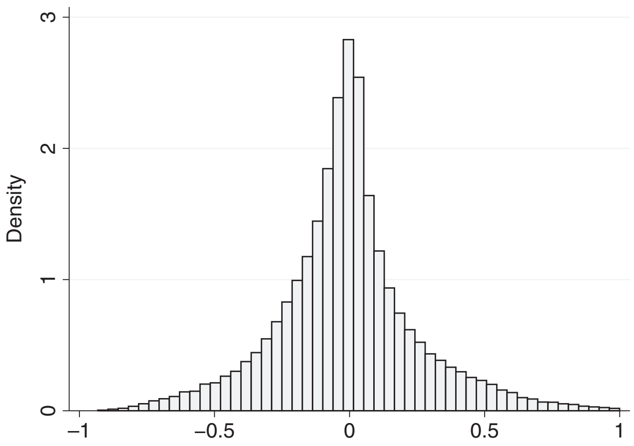

Figure 2: Histogram of the difference between the subjective and predicted 10-year survival probabilities.

In the empirical specifications I disentangle the effects of positive and negative perceptions on preventive care use. The measure of positive perceptions equals the above generated net indicator if that is positive and is zero otherwise. The measure of negative perceptions equals the minus of the net indicator if that is negative, zero otherwise.

4 Although the probit models of survival necessarily exclude the observations of the last 5 waves, the predicted probabilities still can be generated for the whole sample, assuming that the parameters of the survival models remain unchanged across survey waves. The estimated probit models of survival fit the data well. The percentage correctly predicted ranges between 79% and 83%, and the area under ROC (receiver operating characteristic) curve ranges between 84.3% and 87.6%.

The difference between the subjective and predicted survival probabilities can be due to misperception of the true survival probability (including measurement errors), or due to private information related to factors affecting the chances of survival. I return to the analysis of the sources of difference in Section 3.2.2.

The set of graphs presented in Figure 3 illustrates how preventive care use is related to the lagged 10-year survival probability, and to its difference from the predicted survival probability. The graphs present the predicted usage probabilities from estimations of local polynomials along with the 95% confidence interval.[5] As other confounding factors are not controlled for, these graphs cannot reveal causal relations. The graphs indicate that subjective survival probability is positively related to the uptake of mammogram and PAP smear, and negatively to flu shots. The relation of the preventive care use probabilities to the subjective survival probability is different from the relation to the net indicator. Individuals with the most positive and most negative perceptions are the least likely to attend cancer screening, although the confidence intervals indicate large uncertainties. If nonzero values of the net indicator indicate private information then the graphs suggest that both positive and negative private information related to survival are associated with lower likelihoods of attending cancer screening. I investigate these non-monotonic relations further in the following empirical and theoretical analyses.

3 Empirical Analysis

3.1 Main Results

I estimate models of preventive care use, using as main regressors the indicators of positive and negative perceptions as introduced in Section 2. I consider preventive care use to be decided by the patient. Even if physicians have influence through recommending preventive care use (as shown e. g. by Macinko, Starfield, and Shi 2007), the final decision on the uptake of a preventive service is made by the patient. I estimate pooled probit models with robust standard errors clustered at the individual level. In order to avoid omitted variable bias and to capture time trends in preventive care use, I control for a

5 The graphs were prepared with the *twoway lpolyci* command of Stata 13.1, using the default options.

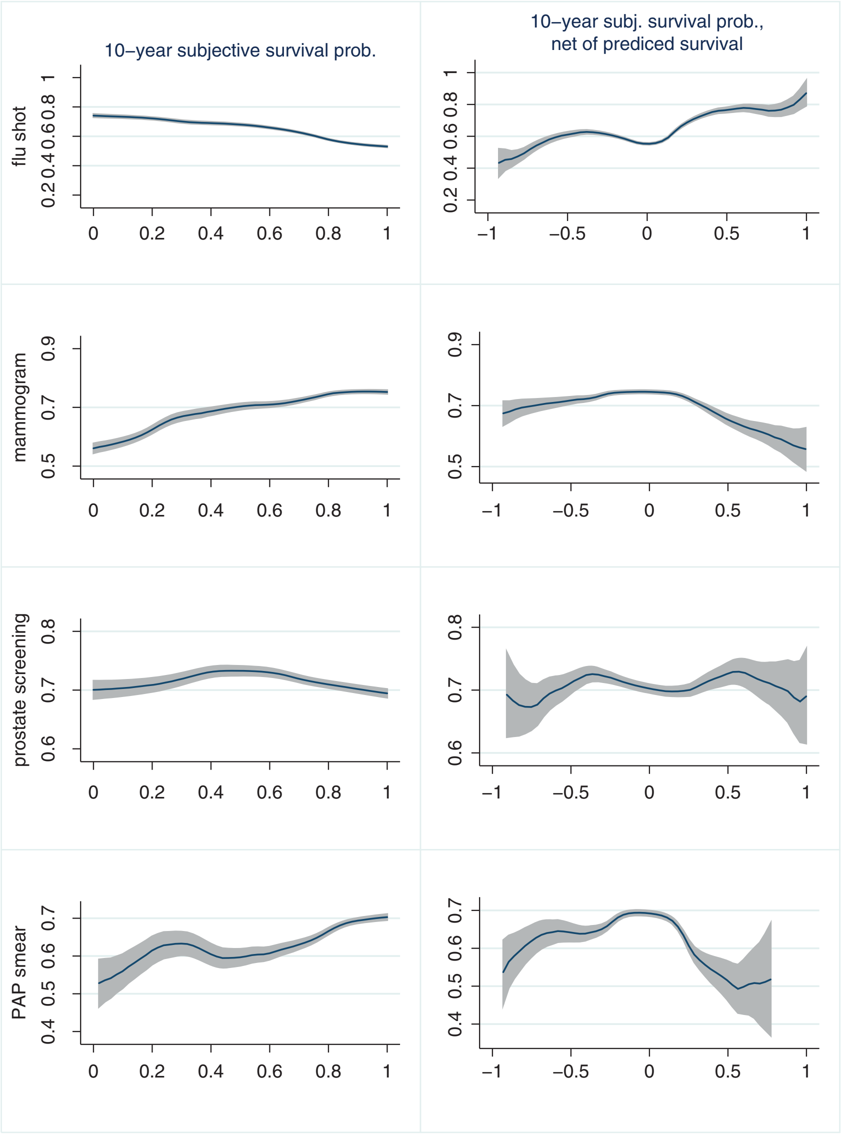

Figure 3: Relation of the subjective survival probability (left panel) and the subjective minus predicted survival probability (right panel) to preventive care use: local polynomial estimator and 95 percentage confidence interval (*y*-axis: probability of use; x-axis, left panel: survival probability; *x*-axis, right panel: difference between subjective and predicted survival probability).

rich set of individual specific characteristics in addition to survey wave dummies (as displayed in Table 3).[6] The control variables ensure that the estimated effects of positive and negative perceptions do not capture the indirect effects of other observable characteristics such as age or education.[7] Each dependent variable is

Table 3: Average marginal effects based on pooled probit models of preventive care use.

	Flu shot	Mammogram	Prostate screening	PAP Smear
Positive perceptions	−0.0609**	0.0132	−0.0119	−0.00979
	[0.0268]	[0.0266]	[0.0289]	[0.0783]
Negative perceptions	−0.0420***	−0.0736***	−0.0656***	−0.0810***
	[0.0128]	[0.0142]	[0.0209]	[0.0224]
Female	0.0557***			
	[0.0014]			
Black/African American	−0.114***	0.0386***	0.0307***	0.0439***
	[0.00576]	[0.00695]	[0.00906]	[0.00954]
Other race	−0.00525	−0.0129	−0.0493***	0.0329**
	[0.00920]	[0.0113]	[0.0132]	[0.0141]
College or higher education	0.0618***	0.0581***	0.0771***	0.0506***
	[0.00408]	[0.00512]	[0.00598]	[0.00700]
ln(income)	0.0137***	0.0252***	0.0288***	0.0191***
	[0.00161]	[0.00189]	[0.00270]	[0.00239]
Age	0.0213***	0.0488***	0.0674***	−0.0287
	[0.00282]	[0.00328]	[0.00442]	[0.0222]
Age squared	−9.89e-05***	−0.000395***	−0.000491***	0.000195
	[2.12e-05]	[2.41e-05]	[3.26e-05]	[0.000195]
Widowed	−0.0494***	−0.0718***	−0.0615***	−0.0436***
	[0.00625]	[0.00667]	[0.0130]	[0.0114]
Single	−0.0557***	−0.0707***	−0.0740***	−0.0474***

(*continued*)

6 The set of included regressors is the same as in the probit models of survival (Section 2), except for the exclusion of parental longevity (capturing inherited traits of longevity in the survival models), subjective health and past preventive care use (omitted to avoid endogeneity bias). Since for most of the respondents preventive care usage is recorded only in the odd numbered waves, I include only four wave dummies in the models. These can capture time effects on preventive care use between waves 4–5, 6–7, 8–9 and 10–11 (with waves 2–3 as the reference category).

7 The decision on preventive care use is supposed to be influenced by the subjective expectations, therefore the predicted survival probability is not included in the model as a separate regressor. The included controls can capture the relation between the predicted survival probability and preventive care use. Nevertheless, the statistically significant marginal effects of negative perceptions are robust to the inclusion of the predicted survival probability in the model.

Table 3: (*continued*)

	Flu shot	Mammogram	Prostate screening	PAP Smear
	[0.00571]	[0.00668]	[0.00912]	[0.00891]
Has child	−0.0224***	0.0213**	0.0263**	0.0250
	[0.00751]	[0.00962]	[0.0114]	[0.0131]
Retired	0.0276***	0.0356***	0.0221***	0.0277**
	[0.00489]	[0.00603]	[0.00750]	[0.0109]
Smoked ever	0.00598	−0.0357***	−0.0239***	−0.0388***
	[0.00390]	[0.00453]	[0.00662]	[0.00695]
Any ADL limitations	0.0193***	−0.0379***	−0.00812	−0.0584***
	[0.00650]	[0.00737]	[0.0103]	[0.0117]
Ever had cancer	0.0423***	0.0473***	0.0664***	0.0240*
	[0.00649]	[0.00806]	[0.0104]	[0.0114]
Ever had high blood pressure	0.0585***	0.0433***	0.0791***	0.0148*
	[0.00385]	[0.00504]	[0.00611]	[0.00716]
Ever had lung disease	0.102***	−0.0398***	0.0398***	−0.0683***
	[0.00770]	[0.00875]	[0.0119]	[0.0136]
Ever had diabetes	0.0853***	−0.0101	0.0202***	−0.0273**
	[0.00590]	[0.00690]	[0.00074]	[0.0110]
Ever had heart problems	0.0613***	−0.0120	0.0168**	−0.0211*
	[0.00565]	[0.00660]	[0.00749]	[0.0110]
Ever had stroke	0.00606	−0.0413***	−0.0360***	−0.0513***
	[0.00903]	[0.0107]	[0.0124]	[0.0195]
Hospital stay, past 2 years	0.0554***	0.0176***	0.0203***	0.0115
	[0.00508]	[0.00600]	[0.00764]	[0.00911]
Nursing home stay, past 2 years	0.0288	−0.0442**	−0.0829***	−0.0576
	[0.0191]	[0.0169]	[0.0273]	[0.0502]
Federal Government health insurance	0.0925***	0.0673***	0.0733***	0.0335***
	[0.00536]	[0.00698]	[0.00873]	[0.00998]
Health insurance from employer	0.0560***	0.0700***	0.0727***	0.0579***
	[0.00418]	[0.00572]	[0.00668]	[0.00717]
Wave 4	0.1000***	0.0451***	0.0472***	0.0284***
	[0.00666]	[0.00885]	[0.0104]	[0.00997]
Wave 6	0.119***	0.0104	0.0144	0.00273
	[0.00670]	[0.00886]	[0.0100]	[0.0104]
Wave 8	0.101***	0.00474	−0.0170*	−0.0544***
	[0.00652]	[0.00874]	[0.0101]	[0.0108]
Wave 10	0.126***	−0.0358***	−0.0695***	−0.0999***
	[0.00632]	[0.00834]	[0.00932]	[0.00981]
Observations	57,927	34,234	23,455	20,794

Note: Clustered bootstrap standard errors in brackets, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

timed one survey wave ahead of the regressors because the reported preventive care use refers to the period since the last interview. This feature of the data also mitigates the problem of reverse causality from the outcome variable to the indicators of positive and negative perceptions. The estimation sample of PAP test is restricted to women aged 50–65. Otherwise the sample covers individuals aged 50 and above.

Is it possible to give causal interpretation to the estimation results? Below I argue that although endogeneity might be present, it is less of a concern in the estimated models than in a specification where subjective survival probability would enter as regressor. Unobserved factors related both to the indicators of positive and negative perceptions and to preventive care use can bias the estimates. Positive attitudes towards preventive care might bias the estimated effect of positive perceptions upwards and negative perceptions downwards, whereas if the usage is triggered by unobserved health problems then the bias is more likely to be in the other direction.[8] Although the empirical strategy I apply can completely eliminate endogeneity only under some strong assumptions, the estimation results are still informative on how preventive care use relates to private information inherent in subjective survival probabilities.

Using the generated indicators of positive and negative perceptions can mitigate the problem of endogeneity. I present this argument in the framework of index function models. Let y denote the binary indicator of preventive care use, $S_{it}^{t+5\star}$ the subjective survival probability to wave $t+5$ (i. e. 10-year ahead), and $\boldsymbol{X}$ the vector of other control variables. Index t refers to time (survey wave), and i to the individual. The probit model with subjective survival probability as regressor is:

8 The endogeneity problems could be mitigated by the estimation of fixed effects models, but data limitations make it difficult to identify the effects of shocks to subjective survival probability. Preventive care use is observed only every four years starting from wave 3. In addition, there is relatively strong persistency in preventive care use. The autocorrelation between the 3rd and 5th wave preventive care use is between 0.34 – 0.54, being the weakest for prostate screening and the strongest for influenza vaccination.

In a related empirical setting, Fang et al. (2007) use the longevity of parents as instrumental variables. The main drawback of using these instruments in the current application is that the early death of a parent can have direct effect on preventive care use, especially if the death was flu related or due to cancer. In addition, indicators of parents' longevity are weak instruments in the current setting.

$$y_{it}^{\star} = \alpha_0 + \alpha_1 s_{it}^{t+5} + X_{it}\alpha_2 + u_{it}, \quad [1]$$

$$\Pr(y_{it} = 1) = \Phi\left(\alpha_0 + \alpha_1 s_{it}^{t+5} + X_{it}\alpha_2\right), \quad [2]$$

where $y^{\star}$ is a latent variable, and Φ (.) is the standard normal cumulative distribution function. Endogeneity can arise from the nonzero correlation between s and u, e. g. due to the joint relation to past preventive care use or to unobserved health behaviours, such as eating habits and physical activity. The net indicator $\tilde{s}$ is generated based on the observed survival S (which is 0 or 1) and observable characteristics $\boldsymbol{Z}$, where $\boldsymbol{Z}$ is a subset of $\boldsymbol{X}$. Again, using the index function framework:

$$S_{it}^{t+5\star} = \beta_0 + \beta_1 y_{it-1} + Z_{it}\beta_2 + v_{it}, \quad [3]$$

$$\Pr\left(S_{it}^{t+5} = 1\right) = \Phi(\beta_0 + \beta_1 y_{it-1} + Z_{it}\beta_2), \quad [4]$$

$$\tilde{s}_{it} = s_{it}^{t+5} - \Pr\left(\widehat{S_{it}^{t+5}} = 1\right). \quad [5]$$

The regressors included in the probit model of observed survival (eq. [4]) are listed in Section 2. The indicators of positive $(\tilde{s}^{pos})$ and negative $(\tilde{s}^{neg})$ perceptions that I use in the empirical analysis are nonlinear functions of $\tilde{s}$: $\tilde{s}_{it}^{pos} = \tilde{s}_{it} \cdot I(\tilde{s}_{it} > 0)$; $\tilde{s}_{it}^{neg} = -\tilde{s}_{it} \cdot I(\tilde{s}_{it} < 0)$, where I (.) is the indicator function. The estimated model is:

$$y_{it}^{\star} = \gamma_0 + \gamma_1 \tilde{s}_{it}^{\mathrm{pos}} + \gamma_2 \tilde{s}_{it}^{\mathrm{neg}} + X_{it}\gamma_3 + w_{it}, \quad [6]$$

$$\Pr(y_{it} = 1) = \Phi\left(\gamma_0 + \gamma_1 \tilde{s}_{it}^{\mathrm{pos}} + \gamma_2 \tilde{s}_{it}^{\mathrm{neg}} + X_{it}\gamma_3\right). \quad [7]$$

If s is endogenous in eq. [1] then the variables $\tilde{s}^{\mathrm{pos}}$ and $\tilde{s}^{\mathrm{neg}}$ can still be correlated with the error term w, but only if that part of the subjective survival probability is correlated with w which cannot be explained by the observable characteristics, i. e. if $\tilde{s}$ and w are correlated. If, for example, in eq. [1] the sole reason of endogeneity is the omitted influence of past preventive care use, and if the influence of past preventive care use is perfectly netted out in eq. [5] due to an identical effect both on the subjective and predicted survival probabilities, then this source of endogeneity is no longer present in eq. [6]. The issue of reverse causality arises in eq. [6]: preventive care use can influence $\tilde{s}^{\mathrm{pos}}$ and $\tilde{s}^{\mathrm{neg}}$ through its effect on the 5-wave survival S.[9] However, the actual survival of a respondent enters into the model only indirectly, through the derivation of the predicted

9 Direct simultaneity bias is not a concern in the estimated models because preventive care use refers to the two-year period after the subjective survival probability was measured.

survival probability indicator (eqs [3] and [4]). Therefore the possible bias caused by reverse causality is negligible.

I present in Table 3 the estimated average marginal effects of eq. [7].[10] The results indicate that apart from the negative effect of positive perceptions on the uptake of flu shot, positive survival perceptions do not have statistically significant effect on the probability of preventive care use. Positive perceptions might decrease the use of preventive care (as is the case for flu shots) because the health and longevity benefits of prevention are lower if someone has private information about factors implying high probability of survival regardless of preventive care use. The results also show that negative perceptions imply significantly lower likelihood of getting a flu jab and attending the three types of cancer screening. If the subjective 10-year survival probability is 10 percentage points lower than the predicted one then that implies 0.42–0.81 percentage points lower probability of preventive care use, ceteris paribus. An explanation can be that an individual perceives a lower chance to enjoy the future benefits of prevention if she has private information about factors that decrease her probability of survival. I return to the underlying mechanisms in Section 4. The nonparametric graphs of Figure 3 already suggested the negative relation between negative perceptions and preventive care use, but could not reveal that this relation is significant and stronger than the relation between positive perceptions and preventive care use.

3.2 Specification Checks

I check the robustness of the results presented in Table 3 and make some extensions to enhance the understanding of the main results. In all specifications I include the same set of control variables as before.

3.2.1 Modified Measures of Positive and Negative Perceptions

First, instead of using the continuous indicators of positive and negative perceptions, I use binary indicators. I define here an individual as having positive

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10 The average marginal effects were calculated with the *margins* command of Stata 13.1. The bootstrap standard errors take into account that the indicators of positive and negative perceptions are based on a first stage estimate. 1000 replications were used in the bootstrapping procedure.

perceptions if the difference between the subjective and predicted survival probability is larger than 0.1 (26% of the respondents with non missing survival probability), and negative perceptions if the same difference is smaller than −0.1 (32% of the respondents with non missing survival probability). Using binary indicators can reduce the noisiness of the regressors of main interest. Apart from flu shots, the results reinforce the negative relation between negative perceptions and preventive care use: people with negative perceptions are 1.6–2.7 percentage points less likely to attend cancer screening, ceteris paribus. The results also indicate that having positive perceptions implies 0.3–1 percentage point lower probability of getting a flu jab or attending prostate screening, although these results are statistically insignificant. I present the marginal effects of interest in the first part of Table 4.[11]

Table 4: Modified measures of positive and negative perceptions: average marginal effects based on pooled probit models of preventive care use.

	Flu shot	Mammogram	Prostate screening	PAP smear
Binary indicators of perceptions				
Positive perceptions (0/1)	−0.00318	0.00445	−0.0104	0.00190
	[0.00799]	[0.00903]	[0.00995]	[0.0184]
Negative perceptions (0/1)	0.00195	−0.0212***	−0.0158**	−0.0265***
	[0.00448]	[0.00570]	[0.00705]	[0.00791]
Observations	57,927	34,234	23,455	20,794
6-year outcomes				
Positive perceptions	−0.106**	−0.00668	−0.0153	−0.00426
	[0.0531]	[0.0524]	[0.0575]	[0.126]
Negative perceptions	−0.0497***	−0.0970***	−0.0750***	−0.119***
	[0.0155]	[0.0166]	[0.0231]	[0.0316]
Observations	57,927	34,234	23,455	20,794
All specifications				
Individual specific controls	✓	✓	✓	✓
Wave dummies	✓	✓	✓	✓

Note: Clustered bootstrap standard errors in brackets, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

11 The results are qualitatively robust to using cutoffs of ±0.2 or ±0.3. With the higher cutoff values some of the estimated effects become slightly stronger.

In the second specification check I return to the continuous measures of positive and negative perceptions, but consider 6-year outcomes instead of the original 10-year outcomes when generating the indicators of positive and negative perceptions. The main benefit of this alternative specification is that the size of the estimation sample increases in the underlying probit models of survival probability. On the other hand, fewer death cases are observed within a 6-year interval. Under this specification the estimated effects of positive and negative perceptions are expected to increase in absolute value because 6-year survival probabilities vary less than the 10-year probabilities. For example, a 10 percentage points deviation in the 6-year survival probability implies stronger private information on survival than the same magnitude of deviation in the 10-year survival probability. The results presented in the second part of Table 4 confirm this expectation: the estimated effects of both the positive and negative perceptions are negative under this specification, and the magnitudes of the significant marginal effects of positive and negative perceptions increase.

3.2.2 Justified versus Unjustified Perceptions

To disentangle the effect of misperception and private information related to survival probability on preventive care use I generate indicators of unjustified and justified positive and negative perceptions. I define the binary indicators of positive and negative perceptions the same way as in Section 3.2.1. Among people with positive perceptions those are defined to have unjustified perceptions who report a new diagnosis of heart problem, stroke, or die during the following 10 years. Otherwise the individual is categorised as having justified positive perceptions.[12] Analogously, an individual with negative perceptions is defined to have unjustified perceptions if she or he is alive 10 years later, and has not been newly diagnosed with heart problem or stroke. Otherwise the individual is categorised as having justified negative perceptions. Justified perceptions can be considered as private information about survival, where "private" information means it cannot be derived from the other observable characteristics. By definition, unjustified and justified survival probabilities cannot be told apart in the last five waves of the HRS. One could argue that the categorisation should be based on the observed survival only since the reported probability refers to the chances of survival. The problem with

12 The terminology is simplified here. Unjustified over- and underestimation of the survival probability can partly be due to misperception, but also due to the random nature of health and survival outcomes. Thus part of the people with " unjustified" positive perceptions might in fact be "unlucky".

this alternative approach, which I check below, is that the actual survival probability cannot be observed, only the actual survival or death. To mitigate this problem, I take into account the occurrence of two chronic health conditions along with the observed survival. The conditions of heart problems and stroke are selected because those are strong predictors of actual survival, and their diagnosis is not likely to be influenced by the utilisation of the analysed preventive care services.[13]

I present in Table 5 the distribution of respondents across the categories and the group-specific average survival probabilities. Pooled linear probability models reveal that men, ever smokers, those reporting some health problems, black respondents, older, widowed or single individuals are more likely to have unjustified positive perceptions, whereas the same characteristics decrease the probability of having unjustified negative perceptions. Biases in subjective survival probabilities in the HRS are also assessed by Elder (2013). Using data from the HRS, in a recent working paper Bago d'Uva et al. (2015) report that individuals with lower levels of education or cognitive abilities are less likely to report accurate survival probabilities, where accuracy is based on observed mortality.

Table 5: Indicators of positive and negative perceptions, respondents aged 50 + .

		Within group mean of 10-year survival probability (%)	
	% of respondents	Subjective	Predicted
Positive perceptions (0/1)	25.80	80.96	49.91
Negative perceptions (0/1)	31.57	47.96	76.32
Neither positive, nor negative perceptions	42.63	79.59	79.89
Justified positive perceptions (0/1)	8.58*	89.06	65.22
Justified negative perceptions (0/1)	18.80*	43.03	73.35
Unjustified positive perceptions (0/1)	12.52*	78.88	44.52
Unjustified negative perceptions (0/1)	18.80*	56.78	85.46

Note: *% of those with non-missing 10-year ahead indicators.

13 This might not be true for diagnosis with cancer, since (early) diagnosis is more likely if someone attends the screening programmes. This could imply reverse causality in the estimated models.

The results presented in the first part of Table 6 indicate that apart from the weakly significant negative effect of unjustified positive perceptions on prostate screening and PAP test attendance, unjustified perception of the survival probability does not have statistically significant effect on the probability of preventive care use. On the other hand, justified negative perceptions imply more than 3.5 percentage points lower likelihood of attending the three types of cancer screening, and these estimates are statistically significant. The small and insignificant estimated effects of unjustified negative perceptions suggest that unjustified expectations (at least in case of negative perceptions) are due to measurement error rather than to strong subjective beliefs on the chances of survival.

Table 6: Justified versus unjustified perceptions: average marginal effects based on pooled probit models of preventive care use.

	Flu shot	Mammogram	Prostate screening	PAP smear
Justified positive perceptions (0/1)	−0.0156 [0.0137]	0.0159 [0.0178]	−0.00339 [0.0181]	0.00585 [0.0239]
Justified negative perceptions (0/1)	−0.00690 [0.00818]	−0.0492*** [0.00990]	−0.0359*** [0.0124]	−0.0662*** [0.0130]
Unjustified positive perceptions (0/1)	−0.00333 [0.0141]	−0.00336 [0.0169]	−0.0301* [0.0181]	−0.0458* [0.0256]
Unjustified negative perceptions (0/1)	0.00313 [0.00764]	−0.00103 [0.00858]	−0.00555 [0.0119]	−0.0101 [0.0105]
Observations	27,981	16,679	11,239	12,334
Positive and negative perceptions based on survival only				
Justified Positive perceptions (0/1)	−0.0101 [0.0121]	0.0205 [0.0149]	−0.00521 [0.0157]	−0.00426 [0.0217]
Justified negative perceptions (0/1)	−0.0191 [0.0130]	−0.0934*** [0.0141]	−0.0643*** [0.0176]	−0.0964*** [0.0215]
Unjustified positive perceptions (0/1)	−0.0133 [0.0161]	−0.0371** [0.0187]	−0.0461** [0.0206]	−0.0649* [0.0347]
Unjustified negative perceptions (0/1)	0.00204 [0.00671]	−0.00817 [0.00787]	−0.00930 [0.0105]	−0.0231** [0.00948]
Observations	27,981	16,679	11,239	12,334
All specifications				
Individual specific controls	✓	✓	✓	✓
Wave dummies	✓	✓	✓	✓

Note: Clustered bootstrap standard errors in brackets, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Next, I differentiate justified and unjustified survival perceptions based only on the observed 10-year survival. For example, those are categorised to have unjustified negative perceptions for whom the generated binary indicator of negative perceptions equals one, but who are alive 10 years after. The estimated negative effect of justified negative perceptions in the models of cancer screening is bigger than before, their estimated effect on flu vaccinations also increases in magnitude but is still statistically insignificant. In addition, using 5% significance level, unjustified negative perceptions are estimated to be significantly negatively related to attending a PAP test. The reason for these changes in the results is that the category of justified negative perceptions is narrower than before – only those are categorised as such who are not alive 10 years after. The results indicate that people with negative perceptions who die within 10 years are ceteris paribus less likely to use preventive care than those who also have negative perceptions, are diagnosed with some health problems within 10 years, but survive. In addition, the (weakly) significant negative marginal effects of unjustified positive perceptions indicate that those who severely overestimate their chances of survival are less likely to use preventive services, implying irrational underutilisation.

3.2.3 Subjective Survival Probability as Regressor

In the baseline empirical specification of Section 3.1, the regressors of central interest are the positive and negative differences between the subjective and predicted survival probabilities. The main benefits of that specification are that positive and negative perceptions are allowed to have different relations to preventive care use, endogeneity concerns are mitigated, and inferences can be made how private perceptions on survival probability affect preventive care use. The aim of the following two specification checks is to provide further insights to the mechanisms driving the baseline results.

First, instead of the measures of positive and negative perceptions, I include the subjective 10-year survival probability as a regressor in the models of preventive care use. The estimated marginal effects of interest are reported in Table 7, indicating that higher subjective survival probability implies higher probability of cancer screening. This finding is in line with the results of Picone et al. (2004). Setting aside the endogeneity issues, the positive relation might be driven by higher marginal benefits of cancer screening. However, these results cannot reveal to what extent these differences are driven by subjective beliefs as opposed to objective survival probabilities. Also, these results cannot capture the non-monotonic relations that the baseline specifications reveal. To investigate non-monotonicities, I re-estimate the models with estimating different coefficients for the five quintiles of the 10-year subjective survival probability in the probit models of preventive care use. The average marginal effects are presented in the second part of Table 7. This extension shows that while higher subjective survival probability generally implies higher probability of preventive care use for all the analysed preventive services, these relations turn to the negative at the top quintile of the survival probability distribution (subjective survival probabilities above 0.96). This is in line with the baseline results and with the predictions of the theoretical model of Section 4: both having very low and very high subjective chances of survival can imply lower demand for preventive care.

Table 7: Average marginal effects of subjective 10-year survival probability based on pooled probit models of preventive care use.

	Flu shot	Mammogram	Prostate screening	PAP smear
10-year subjective survival probability (range: 0–1)	0.00313 [0.0104]	0.0719*** [0.0117]	0.0520*** [0.0140]	0.0841*** [0.0198]
Observations	59,166	34,716	24,205	21,129
Effects by quintiles of 10-year survival probability				
Quintile 1 (0–0.5)	0.0457* [0.0275]	0.118*** [0.0312]	0.0863** [0.0374]	0.0965 [0.0732]
Quintile 2 (0.5–0.7)	0.0336 [0.0473]	−0.0569 [0.0579]	0.0336 [0.0662]	−0.126 [0.0930]
Quintile 3 (0.7–0.87)	−0.0270 [0.0559]	0.186*** [0.0693]	0.0667 [0.0812]	0.232** [0.0958]
Quintile 4 (0.87–0.96)	0.105 [0.102]	0.318** [0.126]	0.308** [0.156]	0.469*** [0.153]
Quintile 5 (0.96–1)	−0.896*** [0.207]	−0.865*** [0.255]	−1.125*** [0.318]	−0.799*** [0.299]
Observations	59,166	34,716	24,205	21,129
All specifications				
Individual specific controls	✓	✓	✓	✓
Wave dummies	✓	✓	✓	✓

Clustered standard errors in brackets, *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$.

The results get close to the baseline results if I use the positive and negative differences between the subjective and gender specific life table survival probabilities as regressors. I use here the same life table survival probabilities as in Section 2. Table 8 shows the estimated marginal effects, which are slightly bigger in absolute value than the baseline results. On the one hand, these differences suggest that the objective elements of subjective survival expectations (which are netted out in the baseline specification but not here) have the same sign of relation towards preventive care use as the subjective elements have. On the other hand, the qualitative similarity of the results to the baseline indicates that the included control variables do a good job in capturing not only the direct effects of observable characteristics but also the indirect effects which work through the predicted survival probability.

Table 8: Differences from life table survival probability: average marginal effects based on pooled probit models of preventive care use.

	Flu shot	Mammogram	Prostate screening	PAP smear
Indicators based on subjective and life table 10–year survival probabilities				
Positive perceptions	−0.0761***	0.000730	−0.0274	0.0143
	[0.0216]	[0.0252]	[0.0258]	[0.0933]
Negative perceptions	−0.0559***	−0.110***	−0.118***	−0.0960**
	[0.0153]	[0.0170]	[0.0228]	[0.0249]
Observations	59,166	34,716	24,205	21,129
Individual specific controls	✓	✓	✓	✓
Wave dummies	✓	✓	✓	✓

Note: Clustered standard errors in brackets, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4 Model of Preventive Care Use

I present an illustrative model that can capture the relation between subjective survival probability and preventive care use. The aim is to enhance our understanding of the complex relations between subjective survival probability and preventive care use, and to relate the empirical findings to the predictions of the theoretical model. The model builds on the Grossman-type models of healthcare demand (Grossman 1972), as preventive care use is considered as an investment in health. The main contributions of the current model are that health and survival probability depend on preventive care use, while at the same time the efficiency of preventive care also depends on survival probability (and health).

I assume that individuals maximise their expected utility based on their subjective survival probability. Subjective survival probability (s) equals the predicted (objective) survival probability plus a deviation between the two: $s = s^{predicted} + \tilde{s}$. Positive and negative perceptions in terms of survival probability as analysed in Section 3.1 (positive and negative $\tilde{s}$) have the same effect in this modelling framework as having higher or lower initial survival probability.

There are two periods. The decision on preventive care use (M) is a dichotomous decision made in period one, and the benefits in terms of health and survival are enjoyed in period two. Preventive services can have three beneficial effects: first, to increase the survival probability, second, to decrease the probability of getting the disease, and third, to mitigate the second period health effects of the disease. I do not consider the potential fourth benefit of decreasing the uncertainty related to second period health. The survival probability is $s + \xi M$ (I assume that max $(s) + \xi \leq 1$), initial health is θs. The probability of getting the disease is $\pi_0-(\pi_1-\pi_2 s) M$ with $\pi_0 \geq \pi_1 \geq \pi_2 \geq 0$, and the second period health in case of getting the disease is $\beta\theta s - \alpha_0 + (\alpha_1 - \alpha_2 s)$ M with $\alpha_0 \geq \alpha_1 \geq \alpha_2 \geq 0$, without the disease it is $\beta\theta s$. The formulations of disease probability and second period health allow the marginal benefit of preventive care to decrease with the initial survival probability (hence also with the initial health).[14]

I assume that consumption equals a fixed income (Y) minus the expenditures on preventive care (pM). Current utility is a linear function of consumption, health, and preventive care use. The utility weights of consumption and health are γ_1 and γ_2. Preventive care use is allowed to have a direct negative effect on utility ($-\gamma_3 M$) due to its unpleasant nature. The second period utility is discounted with a discount factor of δ. Without falling ill with the specific disease, health deteriorates by a factor of $0 < \beta < 1$ due to ageing.

Applying linearity assumptions makes it possible to analytically solve the model. The implications of the model remain similar if Cobb–Douglas utility function is applied; however, the model then can be solved only numerically and such a solution requires further assumptions on the model parameters.

14 π_0 is the probability of getting the disease without preventive care use. This probability decreases with $\pi_1-\pi_2 s$ if preventive care is used. Analogously, α_0 is the health deteriorating effect of the disease without preventive care use, which effect decreases with $\alpha_1-\alpha_2 s$ if preventive care is used.

The maximisation problem is the following:

$$\max_{M\in\{0,1\}} \underbrace{\gamma_1(Y-pM)}_{\text{utility of period 1 consumption}} + \underbrace{\gamma_2(\theta s)}_{\text{utility of period 1 health}} - \underbrace{\gamma_3 M}_{\text{disutility of prevention}} + \delta \underbrace{(s-\xi M)}_{\text{survival probability}} \cdot$$
$$\left[\underbrace{(\pi_0-(\pi_1-\pi_2 s)M)}_{\text{probability of disease}}\left(\gamma_1 Y+\gamma_2 \underbrace{(\beta\theta s-\alpha_0+(\alpha_1-\alpha_2 s)M)}_{\text{period 2 health in case of disease}}\right)+\right.$$
$$\left.+\underbrace{(1-\pi_0+(\pi_1-\pi_2 s)M)}_{\text{probability of no disease}}\left(\gamma_1 Y+\gamma_2 \underbrace{\beta\theta s}_{\text{period 2 health if no disease}}\right)\right] \qquad [8]$$

I consider two types of preventive care. Type 1 care (flu vaccination) decreases the probability of illness, but not the severity of that, thus $\alpha_1=\alpha_2=0$. Type 2 care (cancer screening) on the other hand does not affect the probability of illness, but decreases the severity of that, thus $\pi_1=\pi_2=0$. The following results can be derived.[15]

For type 1 care, $M=1$ is the optimal solution if

$$\underbrace{\gamma_1 p+\gamma_3}_{\text{initial cost of } M} + \underbrace{\delta\xi\pi_0\alpha_0\gamma_2}_{\text{health cost of unavoided disease}} <$$
$$< \underbrace{\delta(s+\xi)\alpha_0\gamma_2(\pi_1-\pi_2 s)}_{\text{health cost of disease avoided by } M} + \underbrace{\delta\xi(\gamma_1 Y+\gamma_2\beta\theta s)}_{\text{value of healthy life gained through } M} \qquad [9]$$

The right-hand side of the inequality is concave in s, and a higher initial survival probability may make preventive care use less likely if π_2 is big. Therefore, if the marginal effect of preventive care on the probability of disease decreases with the initial survival probability then it might not be optimal to use the preventive service for those with the lowest and highest survival probabilities. Also, using that $s=s^{predicted}+\tilde{s}$, no utilisation might be optimal for those with large negative or positive deviations between the subjective and predicted probabilities of survival. This result corresponds to the empirical findings on the demand for flu vaccination. It is also in line with Grossman (1972) who state that "[his] model does not assert that need or illness [...] will definitely be positively correlated with utilization of medical service." If π_2 were negative (implying increasing marginal benefit of care use) then my model would unambiguously predict the preventive care use to increase with initial survival probability.

15 Even if M is allowed to be a continuous variable with $M \in [0,1]$, for both types of care the optimisation problem is convex in M, implying that the optimal preventive care use must be a corner solution, i. e. $M=0$ or $M=1$

For type 2 care, $M = 1$ is the optimal solution if

$$\underbrace{\gamma_1 p + \gamma_3}_{\text{initial cost of } M} + \underbrace{\delta\xi\pi_0\alpha_0\gamma_2}_{\text{health cost of unavoided disease}} < \underbrace{\delta(s+\xi)\pi_0\gamma_2(\alpha_1 - \alpha_2 s)}_{\text{health cost of disease avoided by } M} + \underbrace{\delta\xi\left(\gamma_1 Y + \gamma_2\beta\theta s\right)}_{\text{value of healthy life gained through } M} \qquad [10]$$

The right-hand side of this expression is again concave in s. If the marginal effect of preventive care on the severity of the disease decreases with the initial survival probability ($\alpha_2 \geq 0$ is not negligible) then depending on the other parameters, no use might be the optimal solution for those with the lowest and highest survival probabilities, and also for those with strong negative or positive deviations between the subjective and predicted survival probabilities.

This illustrative model suggests that the estimated negative marginal effects of positive and negative perceptions can all be explained with a utility maximisation model. The empirical results indicate that the marginal benefit of flu shot decreases with survival probability, decreasing benefits are less evident for cancer screening. Also, the robust result that justified negative perceptions decrease the probability of preventive care use can be the outcome of rational decision making, as with lower survival probability the value of healthy life gained through preventive care in eqs [9] and [10] decreases.

5 Concluding Remarks

In this paper, I analyse how preventive care use is related to the subjective survival probability of older people in the United States. Preventive care use might increase the expected lifetime, but the pattern of causation is more ambiguous in the opposite direction. When making a decision on preventive care use, one has to consider the current pecuniary and non-pecuniary costs and the potential future benefits. The decision depends among others on the current survival probabilities. The predictions of a model of preventive care use strongly depend on the assumptions related to the future benefits. If, for example, the marginal benefits are constant, then higher chances of survival are likely to lead to higher demand for preventive care. However, if the marginal benefits are greater for someone in bad health and with low chances of survival then the demand for preventive care might decrease with subjective survival probability. In either case, the optimal decision on preventive care use depends on the chances of survival, which policy makers should take into account when devising preventive care programmes. Depending on the type of the preventive service (its individual and social costs and benefits), it might not be optimal to target people with very low or very high chances of survival, as based on the observable characteristics. This conclusion is based on the theoretical analysis. As an additional layer of the analysis, the empirical findings reveal the importance of private information in subjective survival probability.

The empirical analysis is based on the Health and Retirement Study. My main focus is on the consequences of positive and negative deviations between subjective and predicted (objective) chances of survival. As an extension of the model, I also distinguish justified and unjustified deviations from the predicted survival probability, based on later health and survival. The empirical results suggest that the uptake of flu vaccinations and attendance of cancer screening respond to subjective deviations from the predicted survival probability: those who report lower probability of survival than the predicted survival probability are less likely to utilise preventive services. If the subjective 10-year survival probability is 10 percentage points lower than the predicted one then that implies 0.42–0.81 percentage points lower probability of preventive care use. There is some evidence that positive differences between the subjective and predicted survival probabilities also imply lower likelihood of preventive care use, but this relation is weaker in case of cancer screening. The estimation results can be explained with the utility maximisation model with state-dependent benefits of preventive care. Those who correctly foresee that their expected remaining lifetime is much shorter or longer than what would follow from the observable characteristics might benefit ceteris paribus less from the preventive services because these services have little positive effect on their discounted future utility. Specification checks suggest that the findings are mainly driven by respondents with negative perceptions whose low expectations are justified by later outcomes. There is no clear evidence that unjustified perceptions of survival probability significantly influence the usage of preventive services by people aged 50 and above.

Policy makers and healthcare professionals should thus aim at ensuring that people are well informed about factors such as lifestyle and health behaviours, medical conditions, environmental factors that can influence the chances of survival. Healthcare professionals (general practitioners) could also discuss the longevity perceptions with their patients, and how those influence their decisions of preventive care use. The lack of accurate longevity expectations would lead to sub-optimal decisions on preventive care use.

Due to data limitations, the empirical investigation cannot entirely capture the dynamic relation between survival perceptions and preventive care use. A structural analysis of the dynamic relations remains to future research. Also, the presented theoretical model is only illustratory. Ideally, all the parameters and functional form specifications should be based on empirical observations, which again has heavy data requirements.

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